Portfolio Analysis of Major Mining Industries Using Artificial Neural Networks

A dissertation submitted in partial fulfilment of

the requirement for

Dual Degree (Bachelor and Master of technology)
in
Mining Engineering

by

SAI PRASANNA RATH

Roll No: 710MN1179

Department of Mining Engineering
National Institute of Technology, Rourkela
Rourkela, Odisha-769008

May 2015

Portfolio Analysis of Major Mining Industries using Artificial Neural Networks

A dissertation submitted in partial fulfilment of

the requirement for

Dual Degree (Bachelor and Master of Technology)
in
Mining Engineering

by

SAI PRASANNA RATH

Roll No: 710MN1179

Under the Supervision of

Prof. Dr. D. P. TRIPATHY

Department of Mining Engineering
National Institute of Technology, Rourkela
Odisha, India-769008

May 2015

DEPARTMENT OF MINING ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA
ODISHA, INDIA-769008

CERTIFICATE

This is to certify that the thesis entitled "**Portfolio Analysis of Major Mining Industries using Artificial Neural Networks** " being submitted by Sai Prasanna Rath bearing *Roll no. 710MN1179* to the National Institute of Technology, Rourkela, in the Mining Engineering Department is a bonafide work carried out by him under my supervision and guidance. The research reports and the results presented in this dissertation have not been submitted in parts or in full to any other University or Institute.

Place: Rourkela
Date: 28 May, 2015

Prof. (Dr.) D. P. TRIPATHY
Dept. of Mining Engineering
National Institute of Technology
Rourkela, Odisha, India – 769008

ACKNOWLEDGEMENT

I express my sincere gratitude to my supervisor Prof. Dr. D. P. Tripathy for his invaluable guidance and advice during every stage of this project. I am greatly indebted to him for his directions along with encouragement and support during hard times. An excellent teacher, a tireless researcher himself, Dr. D.P. Tripathy had imbibed these virtues of diligence and enthusiasm in me. I shall forever remain determined to walk on his footsteps.

SAI PRASANNA RATH

ROLL NO: 710MN1179

ABSTRACT

Mining industries are the backbone of Indian economy. Considering the role of mining in India, investing on mining industries will be highly profitable. The financial, technical analysis and price forecasting techniques help the people in clearing the ambiguity between different portfolio options for investment. These traditional techniques are more of theoretical derivation from the results so there is a need for a strong mathematical modelling of the past behaviour of the portfolio options which can then predict the future behaviour. Artificial neural network is one of the best choices available in such conditions. The main objective of any investor being to maximize the returns from his portfolio, artificial neural networks will play an important role in the portfolio analysis.

The project work involved comparison of financial and technical analysis and use of Artificial Neural Network approach for analysing a portfolio in order to select a portfolio option to invest in near future. Here the portfolio options for three mining companies were pre-decided i.e. Coal India Limited, NMDC Limited Enterprises Limited. Then the financial and technical analyses were applied on the stocks of above mentioned companies. Trend lines were also fitted as per the past stock prices and forecasted over to the future. Next the artificial neural network models for each company were modelled over their daily and weekly data sets from October 2011- October 2014. The models were then tested on unknown data sets. An accuracy in the range of 86% - 93% was achieved on the testing data. Predictions were more accurate for a daily basis instead of weekly prediction. At last the results from traditional and ANN methods were combined. Financial ratios implied CIL and NMDC to be the preferable choice while technical indicators supported CIL and AEL. Finally the results from ANN were inferred and it was derived that the CIL stock could be the most preferable choice for investment in near future.

ACRONYMS

CIL	Coal India Limited
NMDC	National Mineral Development Corporation
AEL	Adani Enterprises Limited
ANN	Artificial Neural Networks
RSI	Relative strength index

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER–1

INTRODUCTION

1.1 INTRODUCTION

A portfolio is referred to as a collection of financial assets like stocks, mutual funds, bonds etc. It may be managed by an individual, financial professionals, banks or financial institutions. It can be varied enough to include financial assets of more than one company. This depends on the risk that the investor is ready to take. Therefore before making investments portfolio holders carry out an analysis of the behaviour of the assets of each company within their portfolio. This analysis is called portfolio analysis. Such analysis builds up a clear idea about how much money one should spend and on which assets. The analysis process includes financial and technical analysis. These two methods are widely known and are applied by every financial professional to get an insight about his portfolio.

1.2 MOTIVATION OF THE PRESENT RESEARCH WORK

Mining industries are the backbone of Indian economy. If these industries perform well and are profitable then India will develop and ultimately the people are benefitted. Considering the role of mining in India, investing on mining industries will be highly profitable. For this reason three major mining industries CIL, NMDC and AEL were considered to be present in a portfolio. The main objective of any investor will be to maximize the returns from his portfolio. And through the traditional techniques only a theoretical model about the future trend can be developed. Here there is a need to implement a mathematical model which can read the past performance of the assets and on that basis make a prediction about its future. Artificial neural networks are one of the best choices in such conditions. Thus developing

ANN models for each company in the portfolio and using them for predicting the future trend is highly essential in portfolio analysis.

1.3 OBJECTIVES OF THE PROJECT

- To carryout portfolio analysis of three major mining industries: CIL, NMDC and AEL, using financial ratios and technical analysis.
- To develop artificial neural network models using stock data of CIL, NMDC and AEL for the period October 2011- October 2014.
- To predict the future stock behaviour of CIL, NMDC and AEL based on the financial ratios, technical analysis and ANN models.

CHAPTER-2

LITERATURE REVIEW

Chan et al. (2000) implemented a neural network model using the technical variables for listed companies in Shanghai stock market. In this paper performance of two learning algorithm and two weight initialization methods are compared. The results reported that prediction of stock market is quite possible worth both the algorithms and initialization methods [12].

Siekmann et al. (2001) used fuzzy rules to split inputs into increasing, stable and decreasing trend variables. He implemented a network structure that contains the adaptable fuzzy parameters in the weights of the connections between the first and second hidden layers [14].

Kim & Han (2000) used a genetic algorithm to transform continuous input values into discrete ones. The genetic algorithm was used to reduce the complexity of the feature space [15].

Chenweth (1996) used specialized neural network as pre-processing component and a decision rule base. The pre-processing component determine the most relevant features for stock market prediction, remove the noise, and separate the remaining patterns into two disjoint sets. Next the two neural networks predict the market's rate of return, with one network trained to recognize positive and the other for negative returns [13].

Some work has also been reported in portfolio construction, like the one by Jovina and Akhtar (1996) in their paper proposed a new technology to aid in designing a portfolio of investment over multiple stock markets. For that they used back propagation and recurrent network and also the contextual market information. They developed a determinant using the accuracy of prediction of the neural network and stock return of the previous year and used it to select the stock market among other markets [16].

Panda and Narasimhan (2005) used the artificial neural network to forecast the daily returns of BSE, Sindex. They compared the performance of the neural network with performance of random walk and linear auto regressive models. They reported that neural network outperforms linear autoregressive and random walk models by all performance measures in both in sample and out sample forecasting of daily BSE Sensex returns [17].

Bary (2003) discusses the importance of the cash ratio. Cash earnings will become the key measure of financial performance for many companies [18].

Wiersema (1998) discusses the importance of inventory turnover ratio in his article. He suggests that a high inventory turnover ratio indicates that cash flow is high and business is thriving. He does not directly relate the inventory turnover ratio and stock return, rather he relates the ratio to several other factors that indicate speedy cash flow [19].

Trevino (2002) acknowledges that price earnings ratio is highly correlated with future stock returns. While the cash and inventory turnover ratios are fully objective measures of the company’s success, price-earnings ratio is somewhat more subjective in that it provides a picture of investor’s confidence on the company. He found that a high price earnings ratio indicates that investor feels very good about the company’s direction [20].

Arnott (2003) in his article has mentioned that dividends yield greater returns. His study found future earnings trend to be greater when current dividend payout is greater. This ratio is another subjective measure of financial success. He found there is a high correlation between increasing earnings per share and increasing payout ratios over period of time [21].

Mining industries are one of the major sectors for investment, but application of ANN in this field is limited and there was a need for a study to be done in this sector. ANN along with financial and technical analysis can help a large mass in realizing the approximate behaviour of stock prices within a portfolio. This in turn can guide their buy or sell of stocks. An attempt has been made by picking three major mining industries in the portfolio. They are: Coal India Limited, NMDC and Adani Enterprises limited.

CHAPTER–3

BASIC METHODS FOR ANALYSIS AND INTERPRETATION

3.1 FINANCIAL RATIOS

3.1.1 INTRODUCTION

The significance of ratio analysis lies in the way that it displays information on a near premise and empowers the drawing of inductions with respect to the execution of the firm. Ratio analysis helps in deciding the liquidity position of the firm. A firm can be said to be able to meet its present commitments when they get to be expected. It is measured with the assistance of liquidity ratios. It likewise evaluates the long haul budgetary suitability of a firm. Long- term dissolvability measured by influence/capital structure and benefit ratios. It can focus on the level of effectiveness of administration and use of assets. It is measured by the action ratios. The administration of the firm is worried about the general gainfulness of the firm which guarantees a sensible come back to its proprietors and ideal usage of its benefits. This is conceivable if an incorporated perspective is taken and all the ratios are viewed as together. It can compare different parts of one firm with the other.

3.1.2 SELECTED FINANCIAL RATIOS AND THEIR INTERPRETATION

Table 3.1 Financial Ratios and their interpretations

Ratio	Interpretation
Cash Ratio	The cash proportion shows expanded future profit. More is the ratio, more is the chance that company will survive in any event of short runs. Higher future income brings about an increment in stock cost [1, 2].

Inventory-turnover Ratio	A low stock turnover implies that the company is not delivering at its potential level of effectiveness [1, 2].
Price-earnings ratio	A higher value for ration suggests that the company's direction is convincing to the investors and they will therefore tend to invest more and thereby demand for the stock will increase [1,2].
Dividends-payout ratio	There is a high correlation between increasing earnings per share and expanding payout proportions over time. More is the dividend payout ratio, more will the investors be interested to invest [1, 2].

3.2 TECHNICAL ANALYSIS

3.2.1 INTRODUCTION

Technical Analysis as per the famous Dow Theory, three theorems stand out. They are Price Discounts Everything, Price Movements Are Not Totally Random and "What" is more important than "Why". It plays an important role in understanding and identifying the overbought and oversold price levels as derived from using all the historical data available. The stock price is a combined knowledge of all participants including investors, traders, analysts, market strategists, portfolio managers and many others. Technical analysis uses the information within the price to interpret the market in the future [3, 4].

Price Movements are not absolutely irregular. Most experts agree that prices trend. On the other hand, most professionals likewise recognize that there are periods when price don't drift. The price is the finished after-effect of the fight between the strengths of supply and interest for the organization's stock. The target of investigation is to forecast the direction of the future price. By concentrating on price, technical analysis is a direct approach. The reason why values go up, it is basic, more buyers (i.e. demand) than sellers (i.e. supply) [5].

3.2.2 METHODS

Chart Analysis: Chart analysis (Chartism), as one of the methods for executing technical analysis, incorporates execution of graphs which present business value developments amid a certain period before, as a method for gaining a thought of the conduct of specific securities, and a probability to distinguish a certain guideline in such conduct in light of this example. It includes Support and resistance, pattern lines, Patterns [31].

Technical indicators: Technical indicators, incorporate certain proportions which are utilized for giving grounds and potential outcomes to identifying expected developments of security business sector costs. Huge quantities of specialized indicators are utilized as a part of practice, and individual experts settle on their own decision of these which they consider to be most sufficient at expectation of future price. These markers are estimations which consider price and volume of individual securities. They present money streams, patterns, instability and force. These are utilized as a part of two ways. They are to affirm the value developments through a fitting diagram and to caution for purchase or offer flags in this manner being called leading and lagging indicators [32].

3.2.3 SELECTED TECHNICAL INDICATORS AND THEIR INTERPRETATION

Table 3.2 Technical Indicators and their interpretations

Indicators	**Interpretations**
Linear weighted Moving Average	It is a type of moving average that assigns a higher weighting to recent prices. This indicator usually follows the trend and price movements [6].

Bollinger Band	The interval between upper and lower bands with the middle band is determinate by volatility, typically the standard deviation of the same data that were used for the average. Closer the average line is to the upper band signifies demand is outperforming supplies. And if it is closer to lower band, supplies outperforming demand [7].
Relative strength index	If RSI is greater than 50, average gains are higher than average losses and a value below 50 indicates average losses are winning over average gains. Thus with positive and negative divergences, buy and sell signals can be generated [7].
Momentum	High momentum readings either positive or negative occur when trend is at its strongest. Lower readings are found at the start and end of the trend [7].
DPO indicator	It marks the change of current price with the last closing price. If it is keeping itself well above zero then company stock is doing well and vice versa [7].

3.3 TREND ANALYSIS

3.3.1 INTRODUCTION

Trend analysis helps in finding out the general pattern of a relationship between associated factors or variables. It is also used to forecast the future direction of this pattern for example stock prices.

3.3.2 BEHAVIOUR OF TREND LINES

Patterns are frequently indicated graphically (as line diagrams) with the level of a needy variable on the y-axis and the time period on the x-axis. There are diverse sorts of patterns, including the following: constant, linear, exponential, damped and polynomial.

Constant patterns are those where there is no net build or diminishing. Notwithstanding, there may be regularity or an intermittent variance. Linear patterns demonstrate a consistent, straight-line build or decline. So the pattern line may go up or down, and the point may be steep or shallow. Exponential patterns are those where the information rises or falls not at a relentless rate, but rather at an expanding rate. The x-value (plotted horizontally) is a type of the pattern line recipe to infer the y-value. Damped patterns are those that approach a horizontal asymptote. Polynomial trends are those best modelled by a polynomial equation. They may be second-order (quadratic) equations of the form $y = ax^2 + bx + c$, resulting in a parabolic shape. Polynomial trend lines may also be third order ($y = ax^3 + bx^2 + c$) or higher [23, 32, 33].

3.4 ARTIFICIAL NEURAL NETWORK

3.4.1 INTRODUCTION

The concept of Artificial Neural Networks (ANN) has a biological background. ANNs imitate closely the way that the neurons in human brain function. An ANN is consisted of a set of interconnected processing units, neurons.

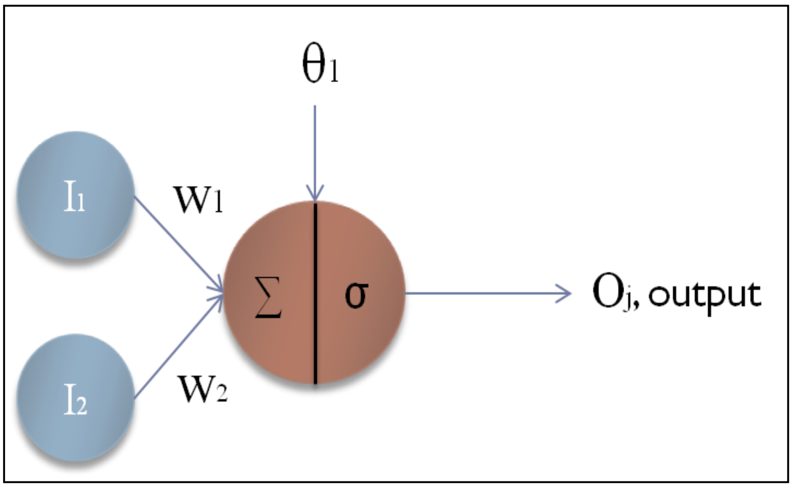

Fig. 1 Basic structure of a single neuron

A neuron is a processing unit that takes a number of inputs and gives a distinct output in Fig. 1

$$O_j = \sigma\ (W1 * I_1 + W_2 * I_2 + \theta_1) \tag{1}$$

$$\sigma(x) = 1/(1+e^{-x}) \tag{2}$$

Each neuron apart from the number of its inputs is characterized by the function f(S) known as activation function.

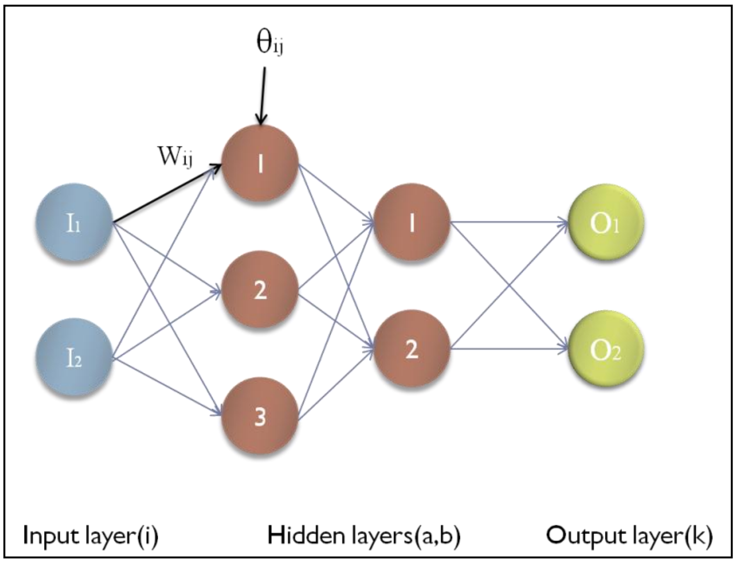

Fig. 2 Artificial neural network showing Input, hidden and output layers with random weights and biases

Each network has got exactly one input layer, zero or more hidden layers and one output layer. All of them apart from the input layer consist of neurons. The number of inputs to the NN equals to the dimension of input samples, while the number of the outputs from the NN defines the number of neurons in the output layer as shown in Fig. 2. The mass of hidden layers as well as the mass of neurons in each hidden layer is proportional to the ability of the network to approximate more complicated functions [11].

3.4.2 TRAINING ALGORITHM

Steps involved in Back propagation algorithm:

- Assign random weights and biases to the connections between nodes.
- Run the network forward with the input data and get to the output.
- For each output node calculate the

$$\Delta_k = O_k(1- O_k)(O_k - t_k) \tag{3}$$

- For each hidden node calculate the

$$\Delta_j = O_j(1- O_j) \sum \Delta_k * W_k \tag{4}$$

$$\Delta W = - \eta * \Delta_k * O_{k-1} \tag{5}$$

$$\Delta\theta = - \eta * \Delta_k \tag{6}$$

$$W + \Delta W \rightarrow W \tag{7}$$

$$\theta + \Delta\theta \rightarrow \theta \tag{8}$$

- Run the above steps in a loop till minimizing the derivative of error function over connective weight factors. Error function is given by

$$E = ½(O_j - t_j)^2 \tag{9}$$

CHAPTER–4

PORTFOLIO ANALYSIS AND TREND ANALYSIS

MATLAB R2013b version (financial analysis app and technical analysis app) and Microsoft excel 2007 were used for carrying out the analysis and forecasting of the stock price.

4.1 DATA SET

Data set includes the stock data from Yahoo Finance for the three industries Coal India Limited, NMDC limited and Adani Enterprises Limited. The data set considered for financial analysis was annual financial sheets of the companies. The data set considered for technical indicators was daily data of each company. The data set considered for Trend analysis was monthly and weekly data of each company. The data set included Opening, Closing, highest, lowest value of the stocks. And volume of the stocks transaction that took place for the time period. The data was taken for three years from **4th Oct. 2011- 4th Oct. 2014** [34, 35, and 36] and was used for analysing their behaviour and makes an approximate prediction of future period price.

4.2 RESULTS OF FINANCIAL RATIOS

The financial ratios which were taken into consideration were:

- Cash ratio
- Inventory turnover ratio
- Price-Earnings Ratio and
- Pay-out ratio

Annual financial sheets of the three companies were observed and the above ratios were computed. These sheets were publicly available in Yahoo finance website [34, 35, 36].

Table 4.1: Annual Financial Ratios from March 2010-14 for Coal India Limited

	Mar'14-Apr'13	Mar'13-Apr'12	Mar'12-Apr'11	Mar'11-Apr'10	Mar'10-Apr'09
	12 months	12 months	12 months	12 months	12 months
Cash ratio	0.59	0.84	0.73	0.61	0.01
Inventory turnover ratio	7.88	22.49	22.47	11.47	18.58
Price-earnings ratio	14.06				
Payout ratio	122.04	90.28	78.31	52.45	58.46

Table 4.2: Annual Financial Ratios from March 2010-14 for Adani Enterprises Limited

	Mar'14-Apr'13	Mar'13-Apr'12	Mar'12-Apr'11	Mar'11-Apr'10	Mar'10-Apr'09
	12 months	12 months	12 months	12 months	12 months
Cash ratio	0.016	0.12	0.008	0.009	0.05
Inventory turnover ratio	11.03	16.14	8.26	6.19	42.96
Price-earnings ratio					
Payout ratio	-	29.61	30.40	40.86	19.57

Table 4.3: Annual Financial Ratios from March 2010-14 for NMDC Limited

	Mar’14-Apr’13	Mar’13-Apr’12	Mar’12-Apr’11	Mar’11-Apr’10	Mar’10-Apr’09
	12 months	12 months	12 months	12 months	12 months
Cash ratio	0.62	0.76	0.83	0.89	-
Inventory turnover ratio	17.70	16.79	24.54	27.37	-
Price-earnings ratio	9.39				
Payout ratio	52.49	43.75	24.55	20.13	20.12

From the ratios for all three companies shown in the Tables 4.1 to 4.3, it can be observed that,

- In case of cash ratio – NMDC > CIL > AEL
- In case of IT ratio – NMDC > AEL > CIL
- In case of PE ratio – CIL > NMDC > AEL
- In case of Pay-out ratio – CIL > NMDC > AEL

The above comparison shows that NMDC or CIL can be the best choice for investment in the near future. They are performing well in terms of production comparatively. They are providing **good dividends** to the shareholders and have high per share income. Better insights on the behaviour of the stocks can be obtained from the application of technical indicators in the next section.

4.3 RESULTS OF TECHNICAL INDICATORS

The indicators taken into consideration were

- Linear weighted moving average

- Bollinger band
- Relative Strength index
- Momentum
- DPO indicator

Technical analysis app of MATLAB was used for plotting these indicators for daily data of the three companies.

Technical Indicators for Coal India Limited from October 2011- October 2014 are given in Figure 4.1(a)-4.1(c).

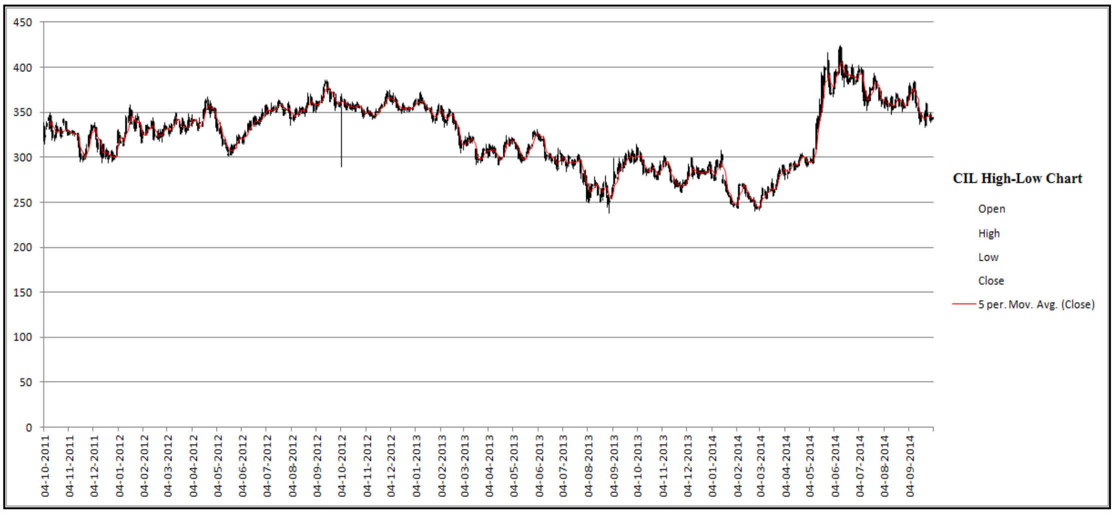

Fig. 4.1(a): Showing the weighted moving average line as red colour almost matching up to the close value of the stock in the high-low chart which has stock values in y-axis and date in x-axis

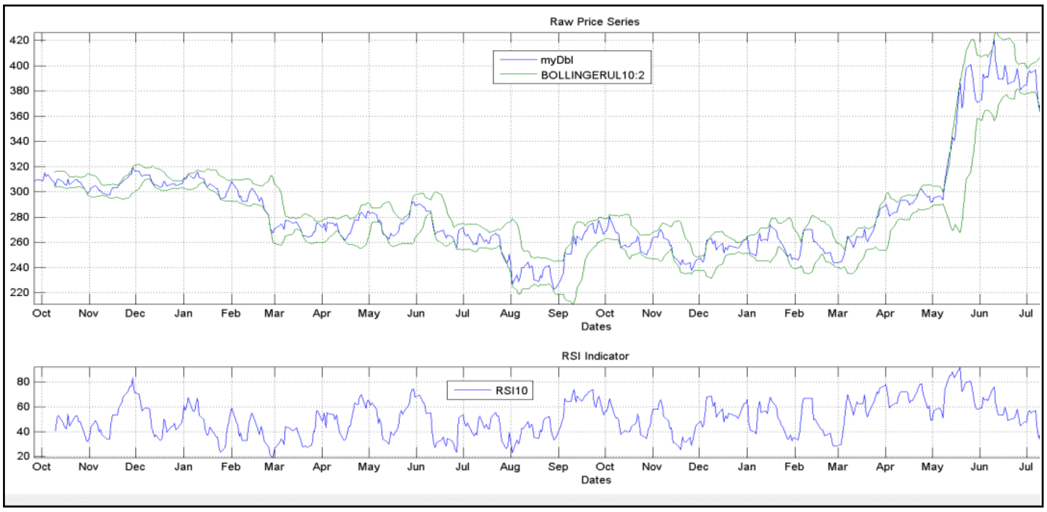

Fig. 4.1(b): Showing the Bollinger band and the RSI chart. In the Bollinger band chart, the green lines represent the upper and lower bands while the linear average as blue.

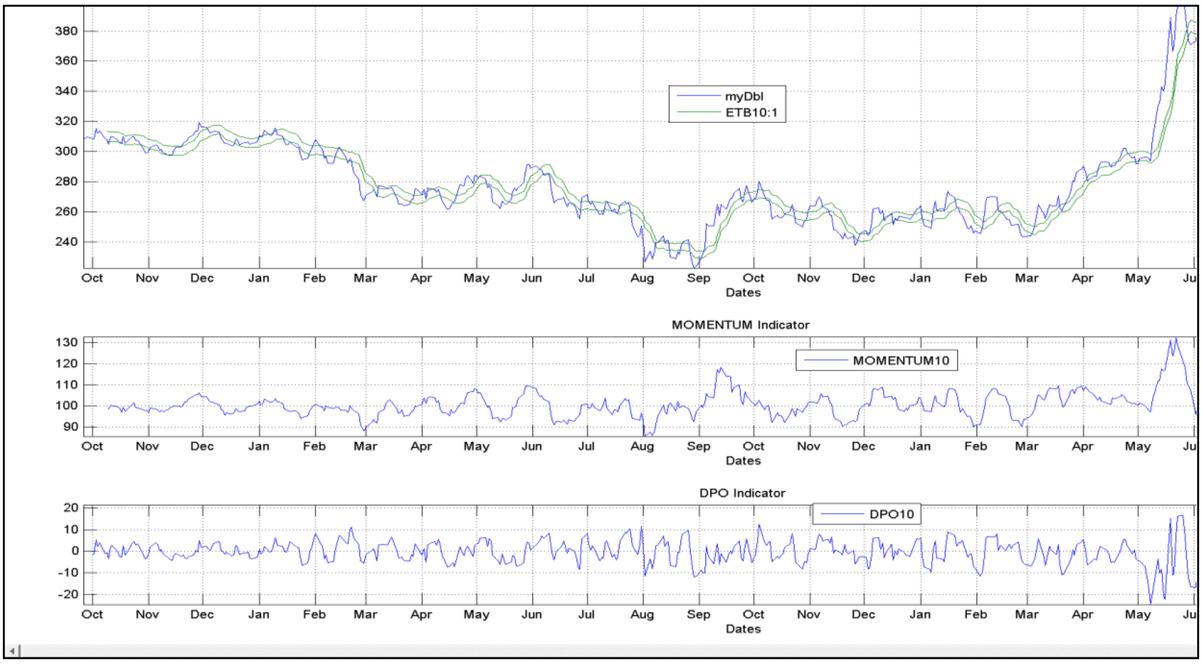

Fig. 4.1(c): Showing the momentum and DPO (price oscillator) indicator.

The use of linear weighted moving average helped in clearly signalizing the trend and price movements with red lines in for CIL Fig. 4.1(a). Then on using the Bollinger band over it helped in getting some hint about the relation between supply and demand. In Fig. 4.1(b), middle band was closer to the lower bound implied a buy signal. The upper and lower bands came closer for CIL, thus decrease in the width of the Bollinger bands represented lower volatility and buy signal. RSI was computed and it was found that RSI varied from 50-60% for CIL Fig. 4.1(c) which implied buy signal. DPO was less than zero for CIL which implied sell signal.

Technical Indicators for NMDC limited from October 2011- October 2014 are given in Figure 4.2(a)-4.2(c).

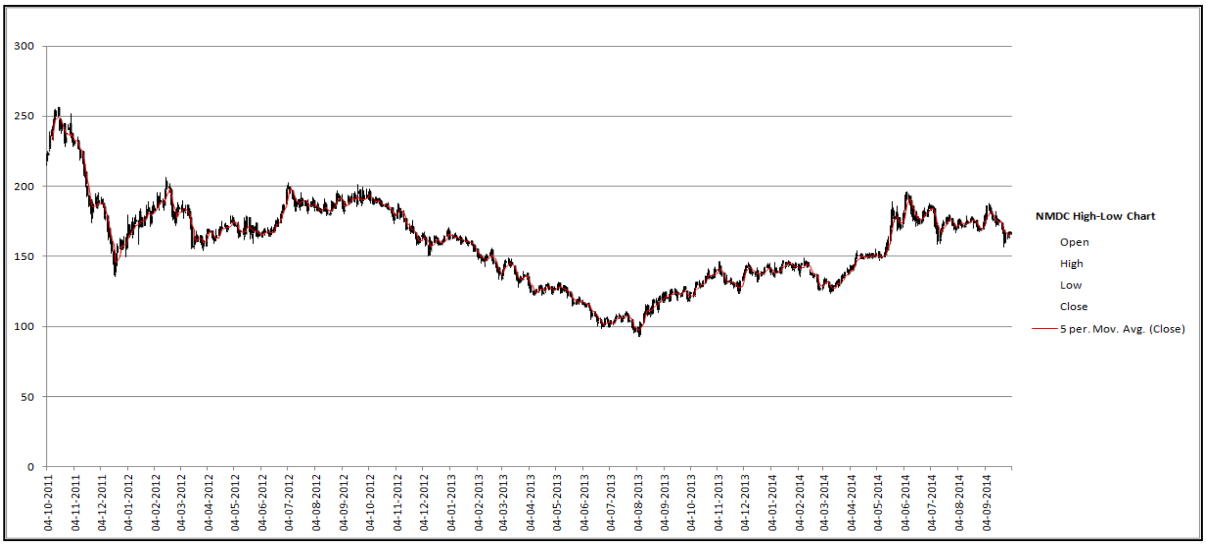

Fig. 4.2(a): Showing the weighted moving average line as red colour almost matching up to the close value of the stock in the high-low chart which has stock values in y-axis and date in x-axis

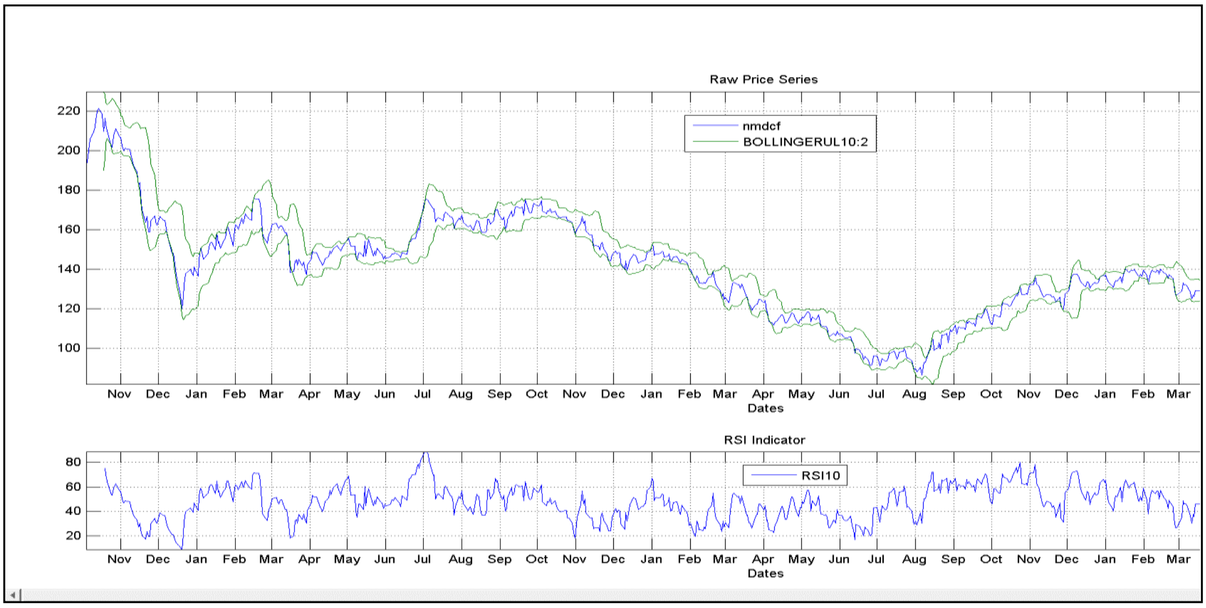

Fig. 4.2(b): Showing the Bollinger band and the RSI chart. In the Bollinger band chart, the green lines represent the upper and lower bands while the linear average as blue.

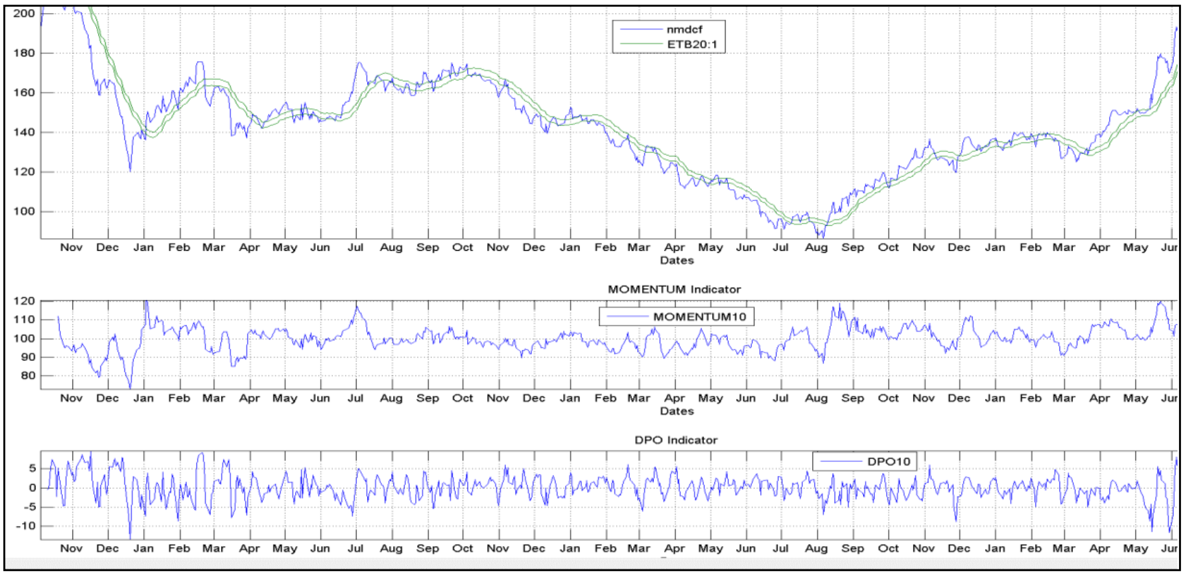

Fig. 4.2(c): Showing the momentum and DPO (price oscillator) indicator.

The linear weighted moving average in Fig. 4.2(a) signalized the trend and price movements with red lines in for NMDC. On using the Bollinger band in Fig. 4.2(b), middle band was closer to the lower bound implied a buy signal. RSI was computed and it was found that RSI varied from 45-55% for NMDC, it is fluctuating between buy & sell signal in Fig. 4.2(c) which implied buy signal. DPO was less than zero for NMDC which implied sell signal.

Technical indicators for Adani Enterprises Limited for October 2011-2014 are given in Figure 4.3(a)-4.3(c).

Fig. 4.3(a): Showing the weighted moving average line as red colour almost matching up to the close value of the stock in the high-low chart which has stock values in y-axis and date in x-axis

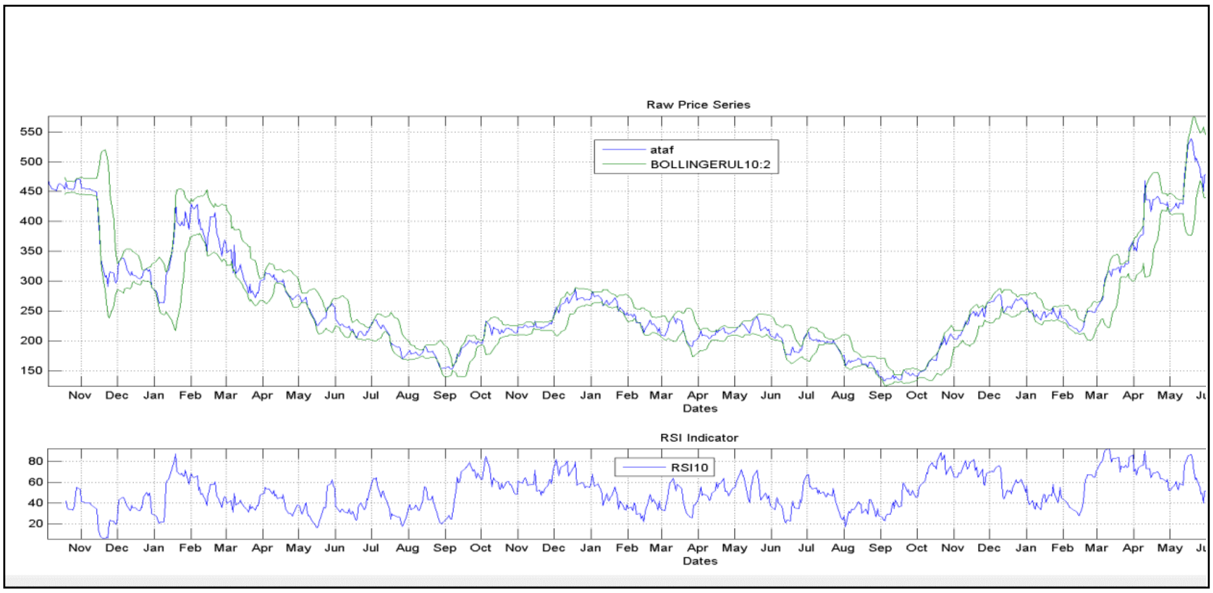

Fig. 4.3(b): Showing the bollinger band and the RSI chart. In the bollinger band chart, the green lines represent the upper and lower bands while the linear average as blue.

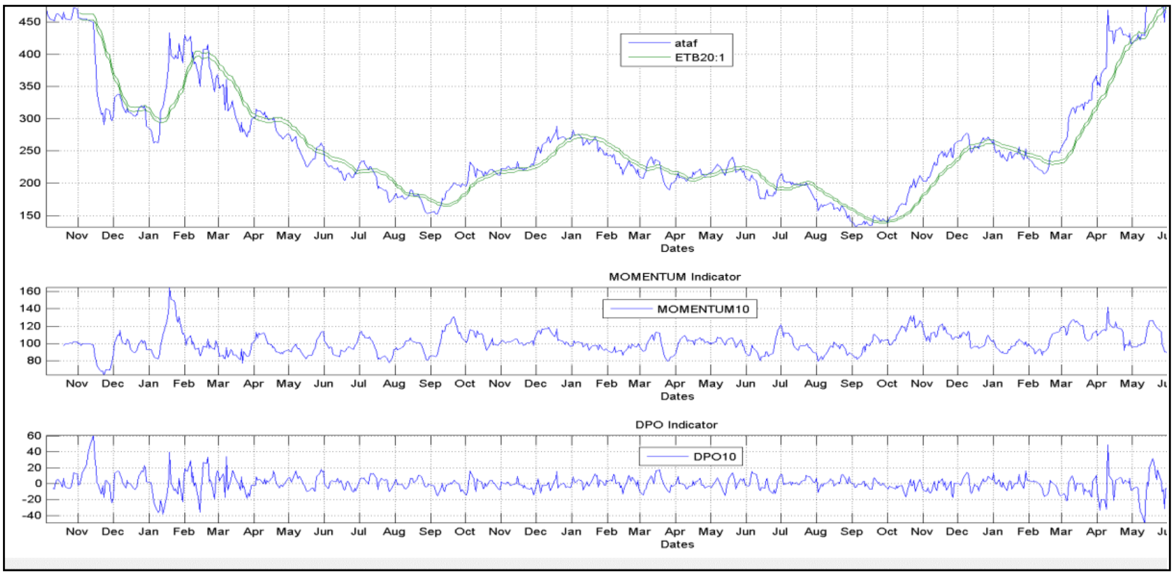

Fig. 4.3(c): Showing the momentum and DPO (price oscillator) indicator.

The use of linear weighted moving average helped in signalizing the trend and price movements with red lines in Fig. 4.3(a). The middle band was closer to the lower bound for AEL showed a buy signal in Fig 4.3(b). The upper and lower bands came closer for CIL and NMDC, it was comparatively wider in case of AEL. Thus wider Bollinger bands represented higher volatility and sell signal. RSI was computed and it was found that RSI varied from 50-

55% for AEL implied buy signal. DPO was greater than zero for AEL which implied buy signal.

4.4 RESULTS OF TREND ANALYSIS

Microsoft excel was used for fitting the monthly and weekly stock price data from October 2011 – October 2014 of CIL, NMDC and AEL. Then the equation obtained was used to forecast prices from 4th October 2014 – 25th October 2014 and from 4th October 2014 – 1st January 2015. The equations obtained by best fitting the price trends for monthly and weekly data are shown in the figures for each company in Fig. 4.4(a) &(b) and Fig. 4.5 (a) &(b) respectively. Polynomial equation best fitted the data with R^2 values shown in respective figures.

Trend analysis and forecasting of the stock price data of Coal India Limited are given in Figure 4.4(a)-4.4(b).

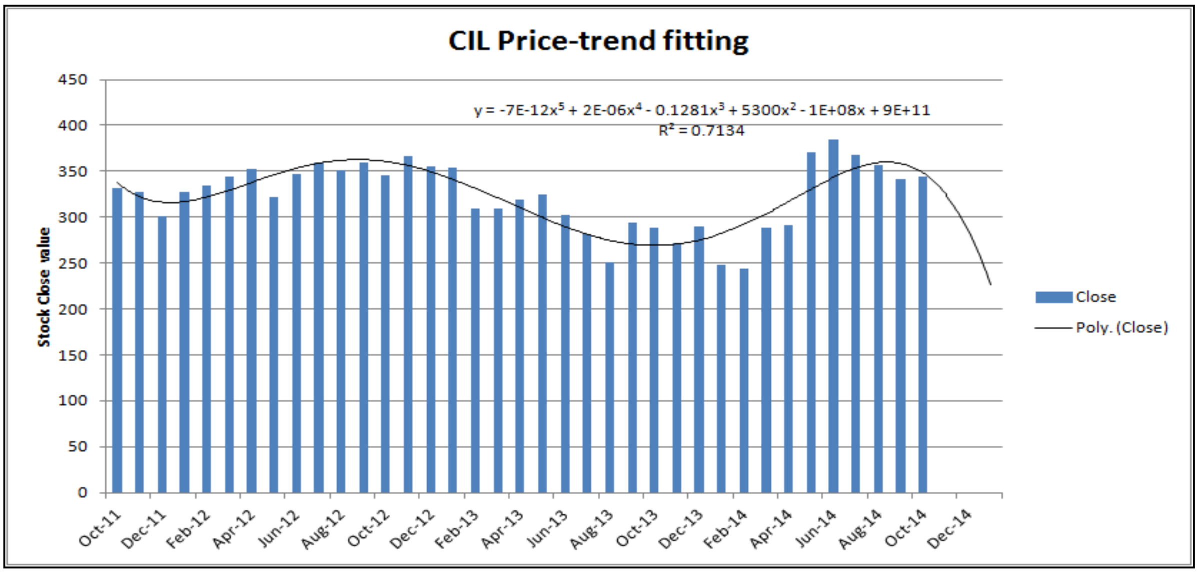

Fig. 4.4(a): Trend fitting on monthly data within October 2011- October 2014

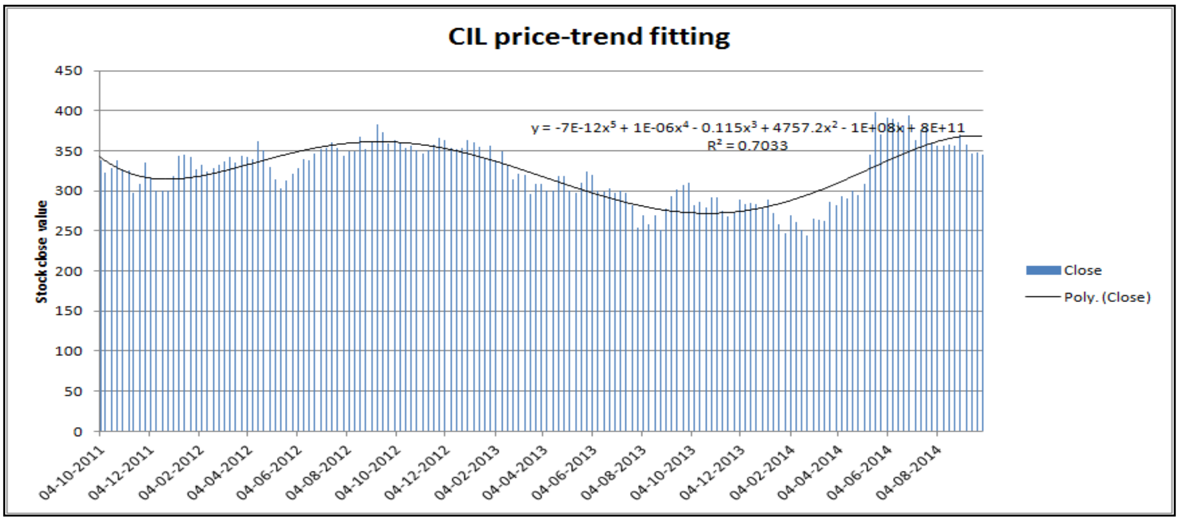

Fig. 4.4(b): Trend fitting on weekly data within October 2011- October 2014

It can be seen for CIL in Fig. 4.4(a) and Fig. 4.4(b), the polynomials implied the prices to be either decreasing or magnitude of change being less in monthly or weekly forecast respectively.

Trend analysis and forecasting of the stock price data of NMDC are given in Figure 4.5(a)-4.5(b).

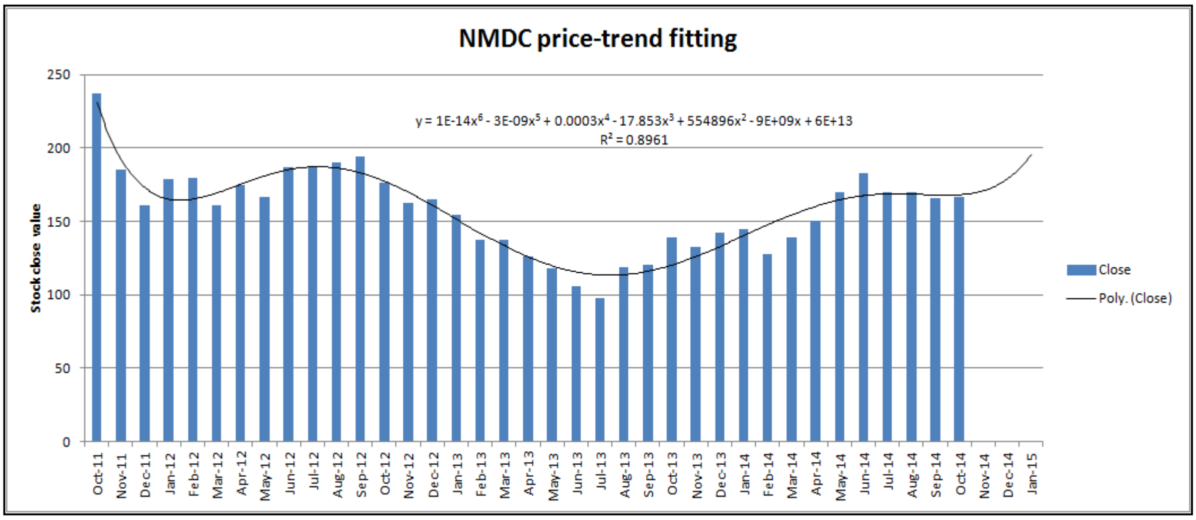

Fig. 4.5(a): Trend fitting on monthly data within October 2011- October 2014

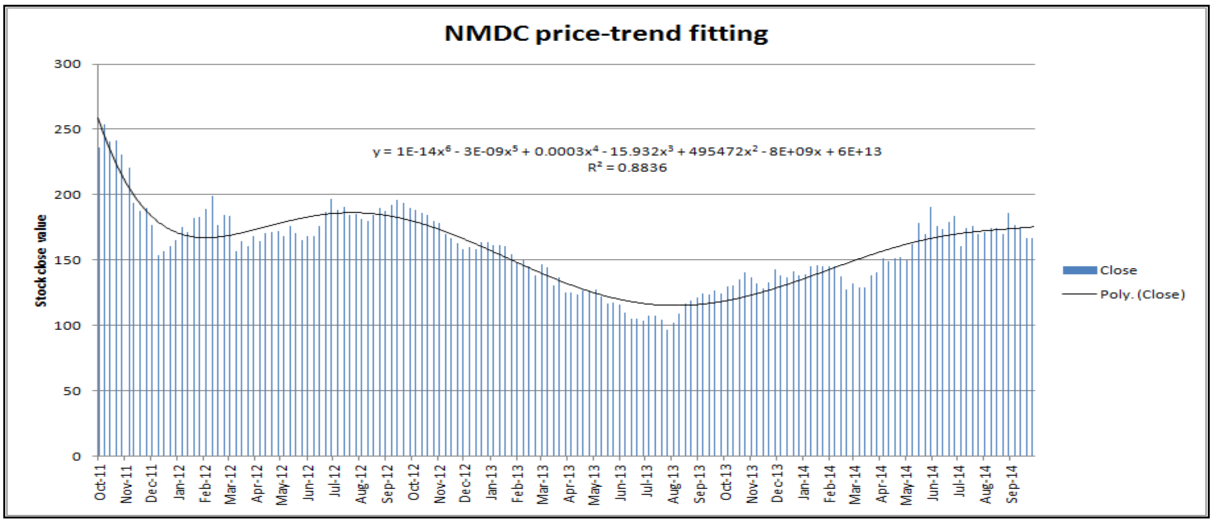

Fig. 4.5(b): Trend fitting on weekly data within October 2011- October 2014

The magnitude of change in price was either less or it increased in case of NMDC in Fig. 4.5(a) and Fig. 4.5(b). Thus it was clear from the forecasted polynomial that investing in NMDC may bring better returns than CIL in the future three weeks. In this trend fitting the major problem was that the trends obtained were of 5th order. The R^2 values of fit for CIL i.e. 0.70 and 0.71 were comparatively lesser than that of NMDC. This implied that the fitting obtained might not be a reliable option for investors before investing large sum of money in any company. Hence ANN modelling was done in order to validate the findings made so far.

CHAPTER–5

ARTIFICIAL NEURAL NETWORK MODELLING FOR PREDICTION OF STOCK PRICE FOR CIL, NMDC AND AEL

5.1 METHODOLOGY

From the previous experiments using financial ratios and technical indicators, it was found that the results still created ambiguity in stock selection. In such situations, ANN come very handy as a support to these results. ANN has been chosen for this purpose because of its non-linear modelling. It can catch various kinds of trend in the time series. It is efficient in learning these trends and it is adaptive.

For developing a neural network model, first of all the input variables were selected. It is a critical factor in the complex non linear structures of the data. It also facilitates the neural network to understand the movements in the time series.

The time series data have been collected from open source online Yahoo finance. The data ranges from October 2011-2014 [34, 35, 36]. It consists of the following fields-

Date; Open, High, Low, Close, Volumes, Adj close

Open, high, low and Volumes were selected as input variables to the neural network.

Close field was selected as output or the variable that would be predicted on the basis of the above mentioned input variables.

The next step is data pre-processing. The performance and reliability of a neural network model also to a large extent depend on the quality of the data used. This facilitates de-trending of the data and highlight essential relationship, so as to facilitate proper network learning.

The linear scaling function used for pre-processing, used the maximum and minimum values of the data series and scaled to an interval of [0,1].

In the next step the processed data were fed as the training set. Out of these data 20% of the last observations were used for validating the model which was obtained on training over the first 80% of the data. Two sets of data for each of the three companies were fed to the system for prediction. One was a daily data set and the other was a weekly data set. Both ranged from October 2011- October 2014 [34, 35, and 36]. These two data sets were considered in order to have better comparison of behaviour of ANN on stock markets for either a short period or long period prediction.

In the last step two sets of new test data i.e. daily and weekly data were collected from the same source ranging from October 2014 - December 2014 [34, 35, and 36]. The close value of the stocks of each company was predicted over this period for both the sets. Then the actual and predicted close values of stocks were plotted on a graph which can be found in the following pages.

5.2 RESULTS

ANN modelling of the weekly data set of Adani Enterprises Limited are given in Figure 5.1(a)-5.1(b).

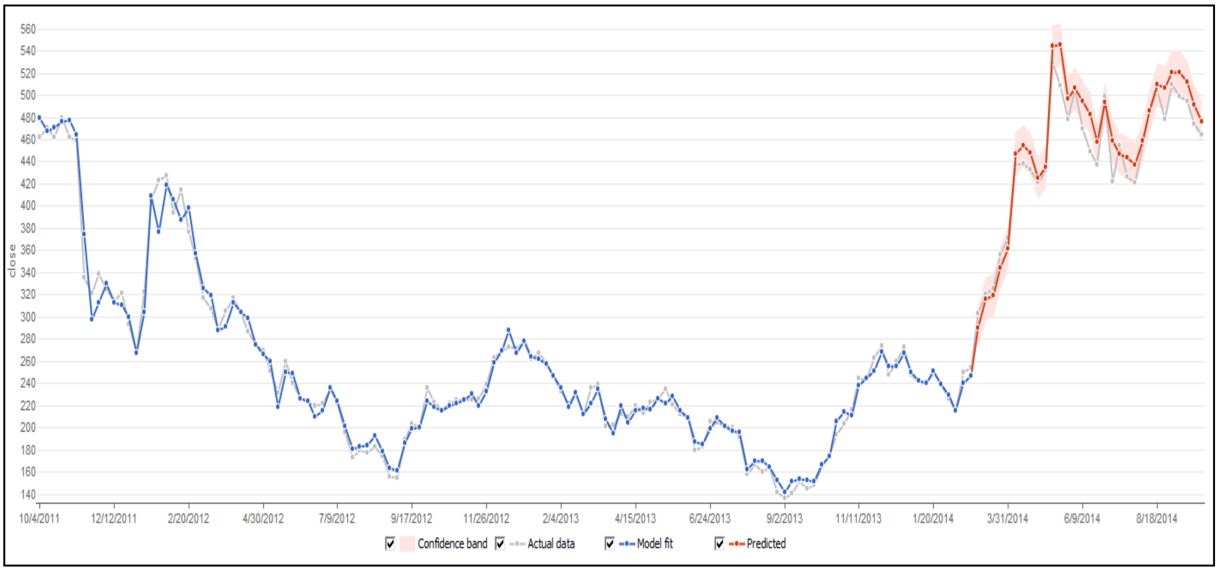

Fig. 5.1(a): 80% of the data for training shown in blue colour and last 20% shows the validation test shown in red colour

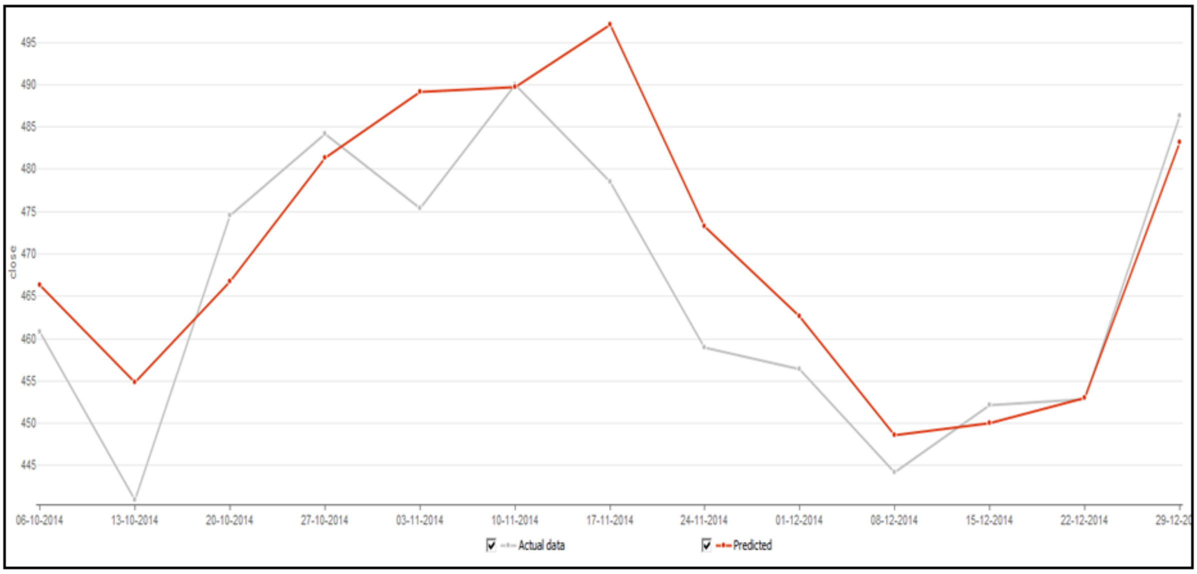

Fig. 5.1(b) Predicted and actual data given by the above trained model

ANN modelling of the daily data set of Adani Enterprises Limited are given in Figure 5.2(a)-5.2(b).

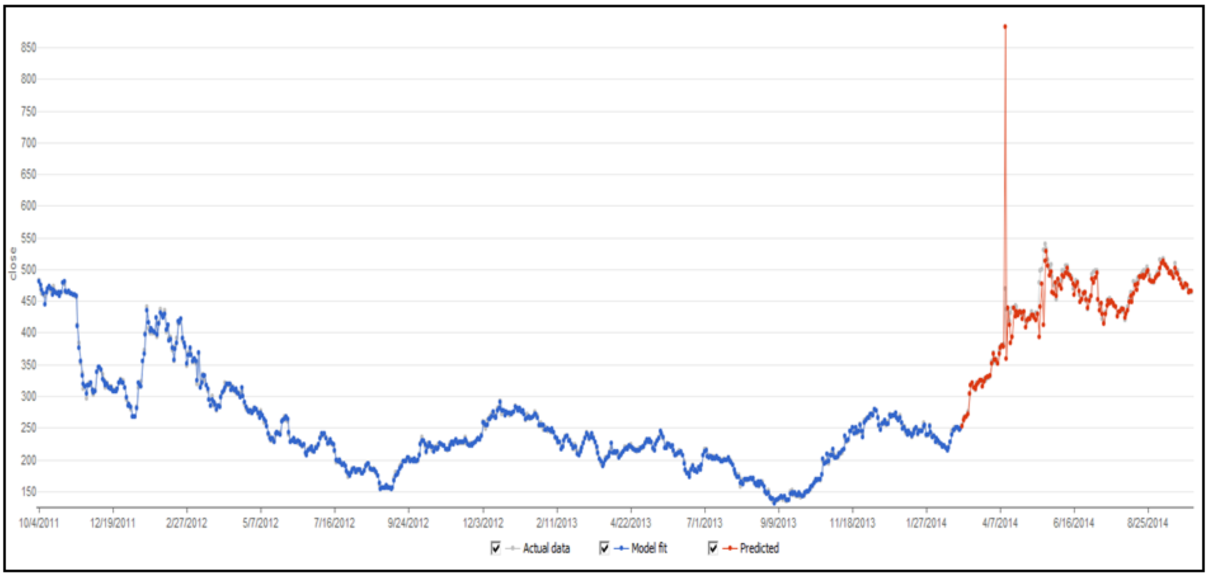

Fig. 5.2(a): 80% of the data for training shown in blue colour and last 20% shows the validation test shown in red colour

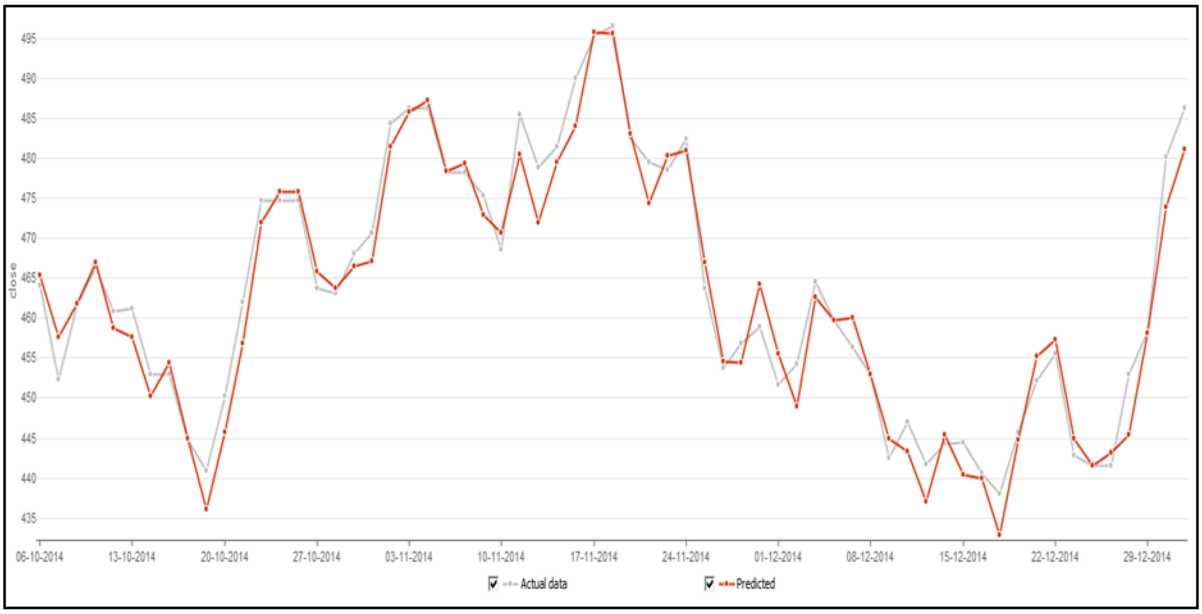

Fig. 5.2(b): Predicted and actual data given by the above trained model

ANN modelling of the weekly data set of Coal India Limited are given in Figure 5.3(a)-5.3(b).

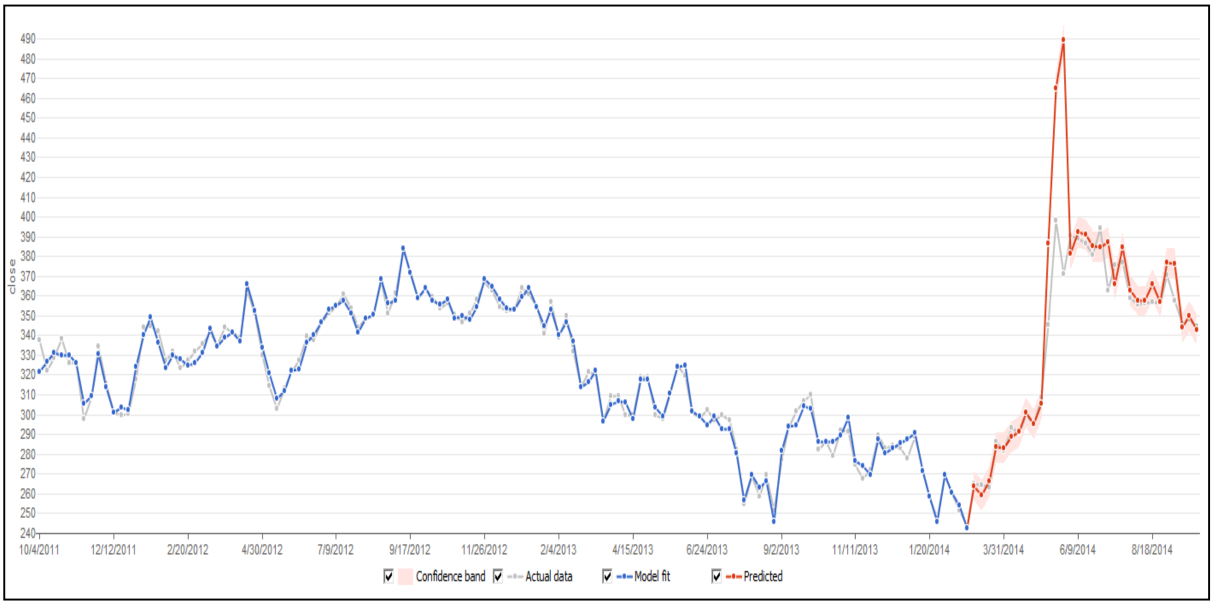

Fig. 5.3(a): 80% of the data for training shown in blue colour and last 20% shows the validation test shown in red colour

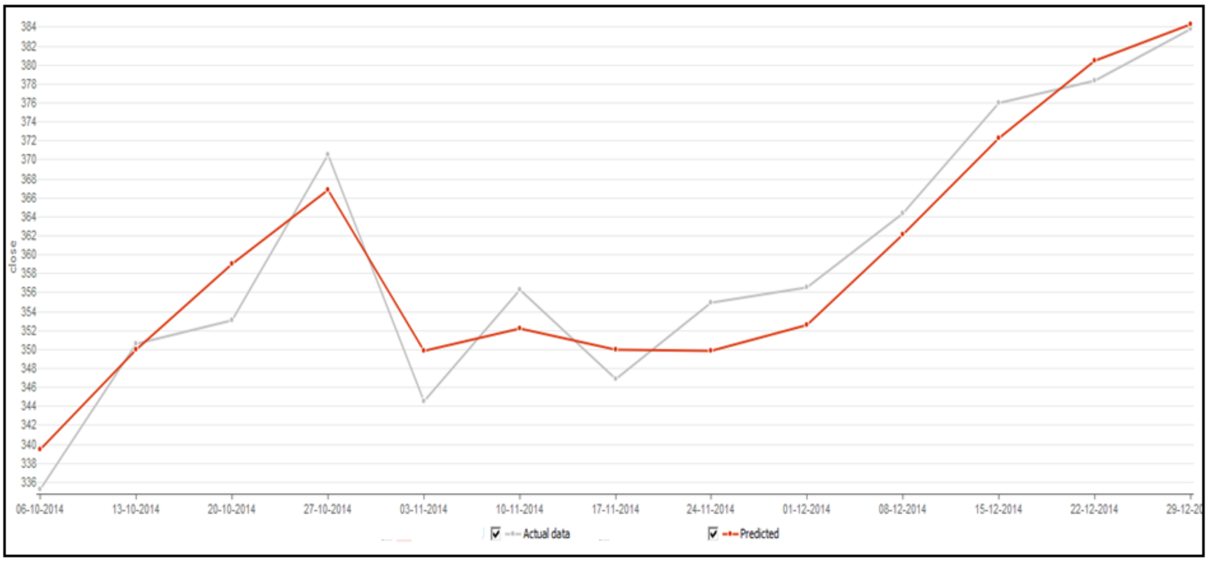

Fig. 5.3(b): Predicted and actual data given by the above trained model

ANN modelling of the daily data set of Coal India Limited are given in Figure 5.4(a)-5.4(b).

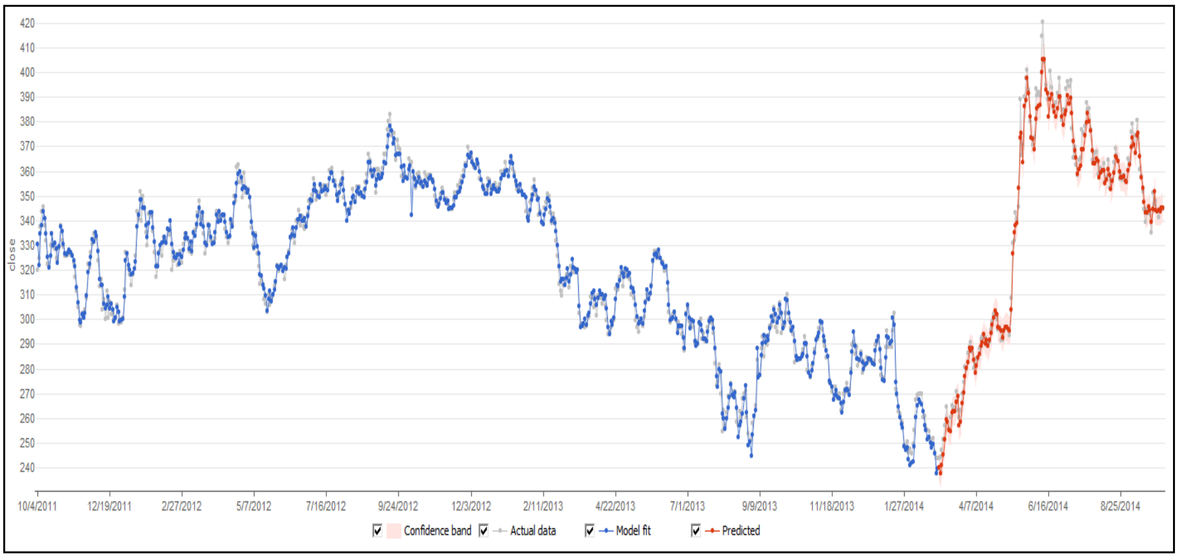

Fig. 5.4(a): 80% of the data for training shown in blue colour and last 20% shows the validation test shown in red colour

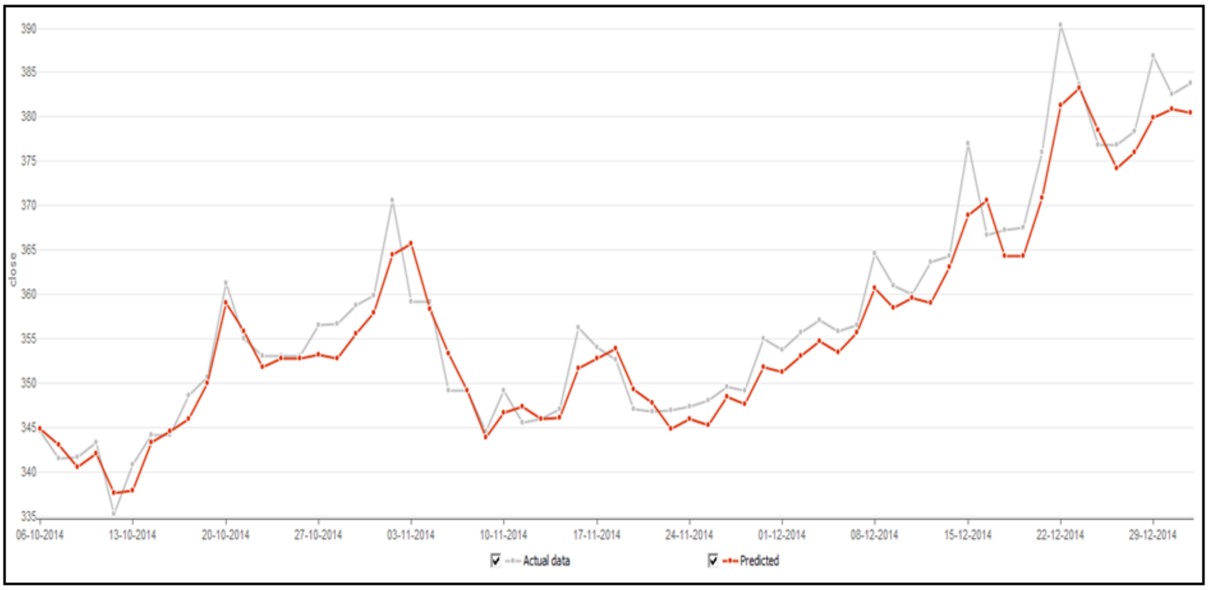

Fig. 5.4 (b): Predicted and actual data given by the above trained model

ANN modelling of the weekly data set of NMDC limited are given in Figure 5.5(a)-5.5(b).

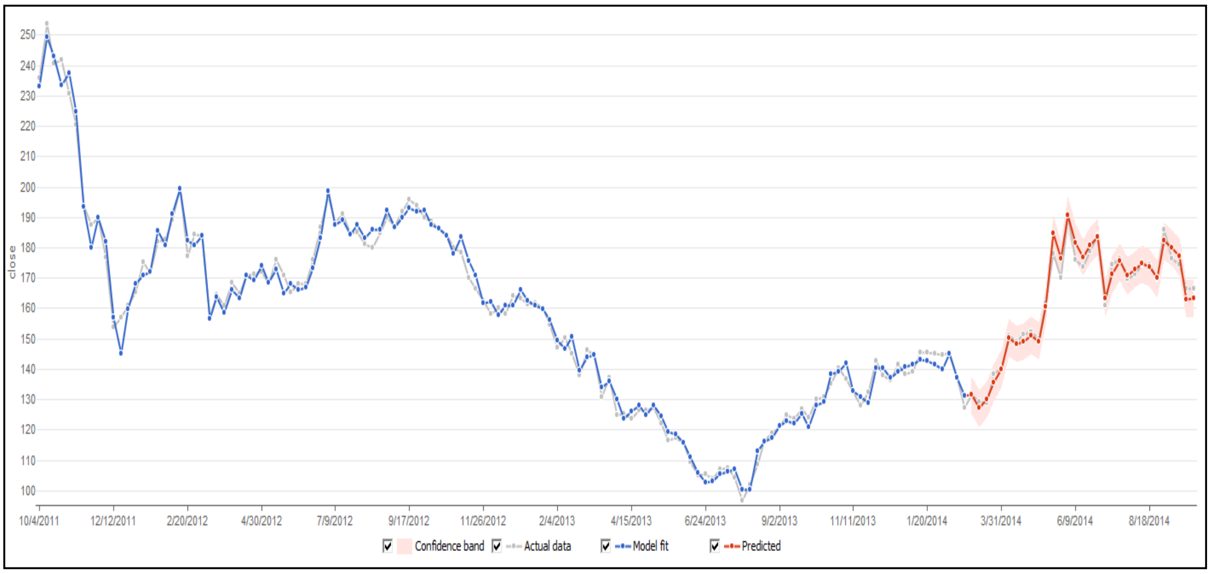

Fig. 5.5(a): 80% of the data for training shown in blue colour and last 20% shows the validation test shown in red colour

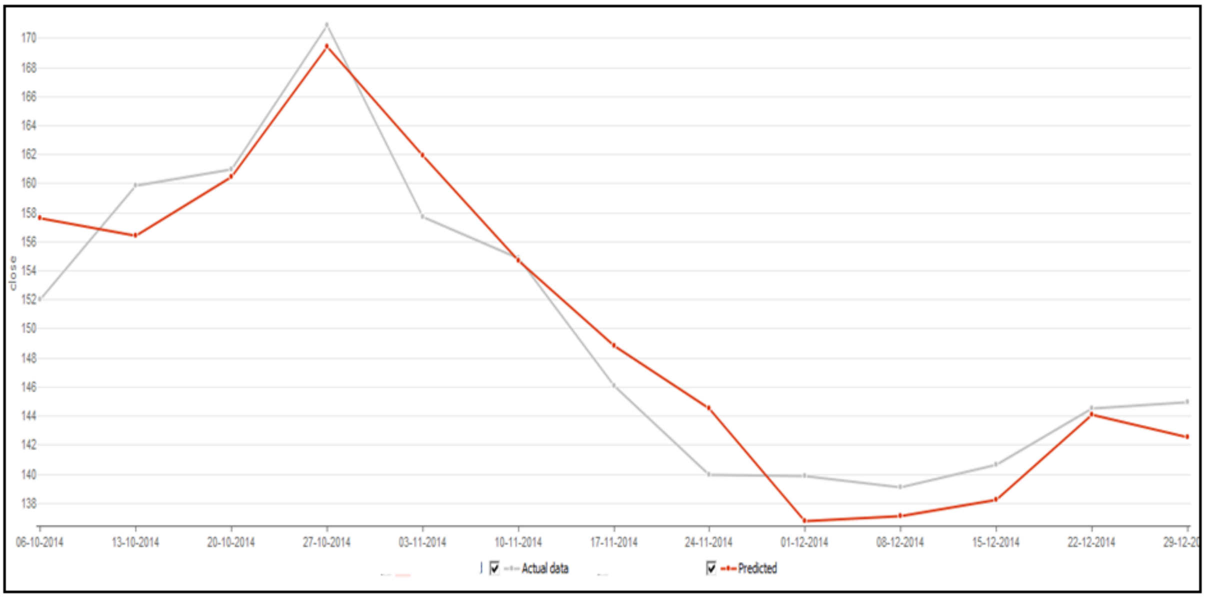

Fig. 5.5(b): Predicted and actual data given by the above trained model

ANN modelling of the daily data set of NMDC limited are given in Figure 5.6(a)-5.6(b).

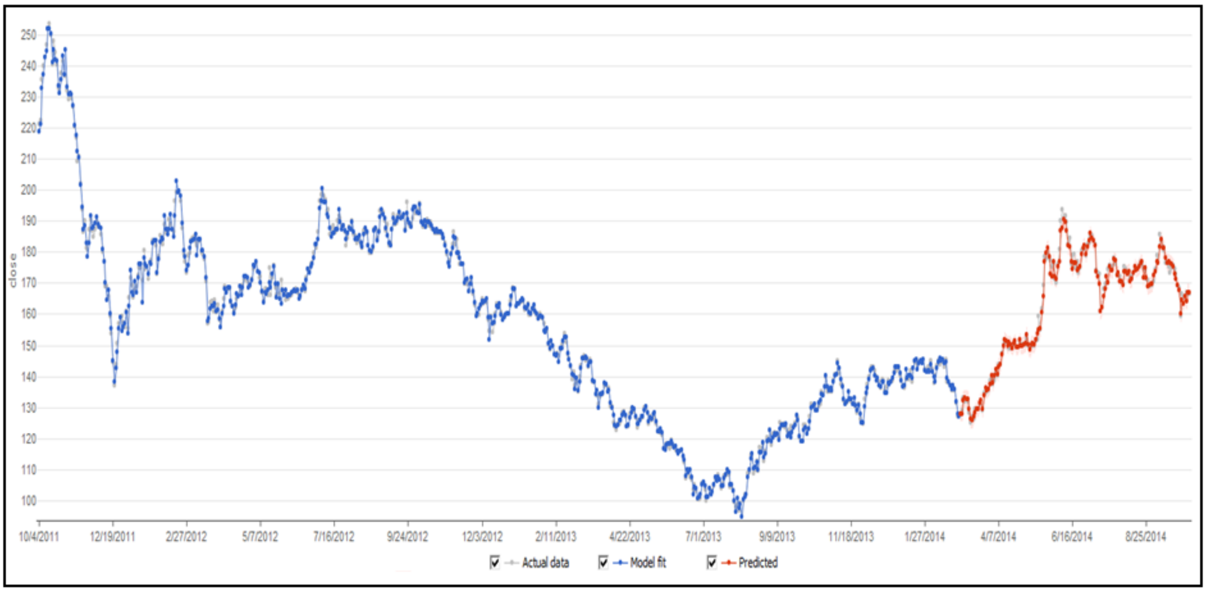

Fig. 5.6(a): 80% of the data for training shown in blue colour and last 20% shows the validation test shown in red colour

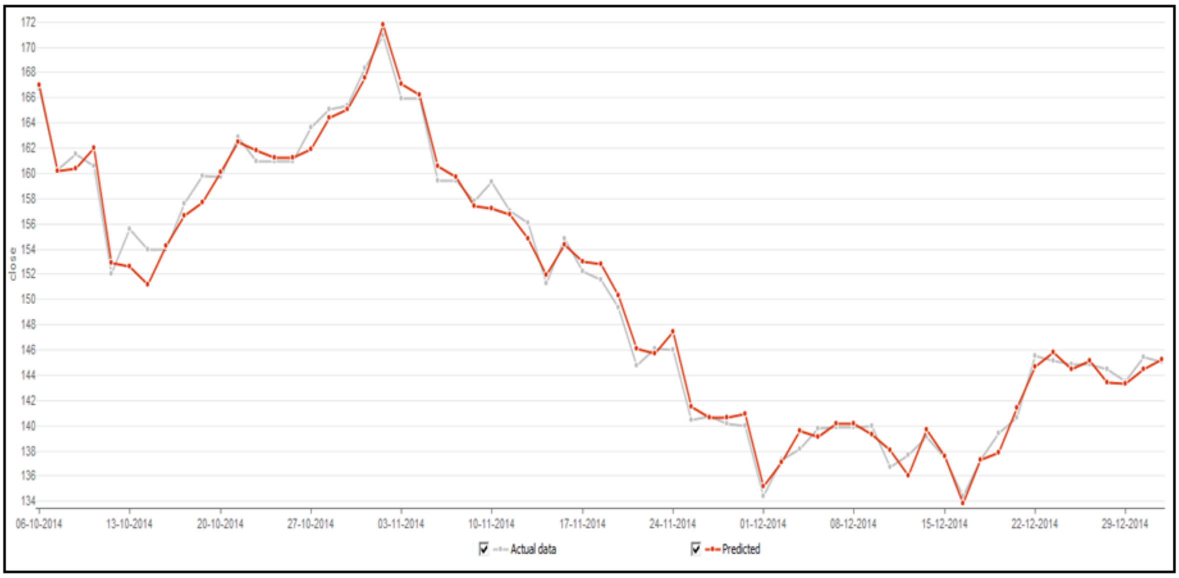

Fig. 5.6(b): Predicted and actual data given by the above trained model

5.3 DISCUSSION

The graphs in the previous section give a brief insight of the behaviour of the stock prices of all the three companies. This helped in making a clear comparison between the stocks present in the portfolio. The Fig. 5.1(a), Fig. 5.3(a) and Fig. 5.5(a) shows the behaviour of the stock prices on a weekly basis. These weekly ANN models showed R^2 values of 0.98, 0.991 and 0.992 respectively for the training set of the three companies. In case of the testing sets, these models showed R^2 values of 0.92, 0.90 and 0.80 for the respective companies in Fig. 5.1(b), Fig. 5.3(b) and Fig. 5.5(b) whereas the R^2 values for the testing of daily datasets based trained ANN models were 0.94, 0.99 and 0.95 respectively in Fig. 5.2(b), Fig. 5.4(b) and Fig. 5.6(b). Then the co-efficient of determination of both the testing results i.e. daily and weekly data sets were compared and it was found that models developed on daily data sets were more reliable than those developed on the weekly data sets for corresponding companies.

Fig. 5.7 Actual stock value variation shown in Google Finance for the testing period (Oct. 2014 – Dec. 2014)

Moreover the analysis that was made using technical and financial measures in the beginning showed CIL and NMDC stocks to be more preferable for buying, but the predictions made by ANN in Fig. 5.2(b), Fig. 5.4(b) and Fig. 5.6(b) show that there may be decrease in the stock price of NMDC which may lead to loss for those who invest on it in the near future. The predictions show either stable or increasing performance of CIL and AEL stocks in the near future, thus making them the probable choice for investment. These behaviours of the stocks can also be verified from the actual statistics shown by Google finance in their chart reports in Fig. 5.7 [33]. The predicted values of the stocks were compared with the actual values for the testing period Oct. 2014 – Dec. 2014 [34, 35, and 36]. The accuracy of the models on the testing data sets varied between 86% and 93%.

CONCLUSION

The primary objectives of the project were to analyse the behaviour of the portfolio options using financial ratios and technical variables and to develop ANN models for each portfolio options so as to predict their future behaviour. From the analysis carried out, the following conclusions can be drawn:

- On comparing the financial ratios, it was found that NMDC and CIL were preferable choice for investment in near future because of comparatively higher production, dividends and per income share.
- On applying technical analysis, it was found lower volatility for CIL and NMDC and company share buy signal for all three. RSI showed higher buy signal for CIL and AEL, but weaker buy signal for NMDC. Hence, CIL and AEL could be preferable choice for investment.
- On applying trend analysis, it was found that the forecasted stock prices of NMDC remains same or increases while for CIL it decreases. But the polynomials obtained for the past time series were of 5^{th} order and R^2 value were much less than 1. So the fitting was not strong enough to be relied on for future investment.
- On applying artificial neural networks, predictions showed rising stock prices for CIL and AEL while decreasing in case of NMDC. Accuracy of 86% to 93% was obtained over the testing data sets.
- Combining all above conclusions it was found that CIL may be the most preferable choice for investment as compared to other portfolio options for incurring investment in the near future. It was found that ANN models developed over daily data sets predicted the stock prices with better accuracy than models developed over weekly data sets. The results depicted that ANN may not be a good choice for predicting stock price for the long time period rather than the short term.

REFERENCES

1. Turk, A., 2006, The Predictive Nature of Financial Ratios. The Park Place Economist, 14, 96-104.
2. Nidhyananth, D., Aarthi, C., 2012, A Study on Financial Performance Using Ratio Analysis at Sakthi Sugar Ltd., Sivagangai Unit, IOSR Journal of Business and Management, 01-06.
3. Achelis, S. B., 2001, Technical Analysis from A to Z. New York: McGraw Hill.
4. Sewell, M., 2007, Technical Analysis, http://www.technicalanalysis.org.uk/technical-analysis.pdf.
5. Sewell, M., 2001, Technical Analysis. http://www.technicalanalysis. org.uk/.
6. Zhu, Y., & Zhou, G., 2009, Technical Analysis: An Asset Allocation Perspective on the use of Moving Averages. Journal of Financial Economics, 92(3), 519-544.
7. Andersen, T. G., & Bollerslev, T., 1997, Intraday Periodicity and Volatility Persistence in Financial Markets. Journal of Empirical Finance, 4(2), 115-158.
8. Liaw, S., 2012, Technical Analysis: An Asian Perspective, http://ink.library.smu.edu.sg/cgi/viewcontent.cgi?article=1087&context=etd_coll.
9. Plummer, T., 1993, The Psychology of Technical Analysis: Profiting from Crowd Behavior and the Dynamics of Price. Probus Publishing Company.
10. DAS, S., 2010, Analysis and Interpretation of Financial Statements: Case Studies (B. Tech. Project, National Institute of Technology, Rourkela).
11. Widrow, B., 1988, DARPA Neural Network Study. AFCEA International Press, Fairfax, VA.
12. Chan, M. C., Wong, C. C., & Lam, C. C. (2000), Financial Time Series Forecasting by Neural Network using Conjugate Gradient Learning Algorithm and Multiple Linear Regression Weight Initialization, Computing in Economics and Finance, Vol. 61.
13. Chenoweth, T., Obradovic, Z., & Lee, S. S. (1996). Embedding Technical Analysis into Neural Network Based Trading Systems. Applied Artificial Intelligence, 10(6), 523-542.
14. Siekmann, S., Gebhardt, J., & Kruse, R. (1999). Information Fusion in the Context of Stock Index Prediction, Symbolic and Quantitative Approaches to Reasoning and Uncertainty, Springer Berlin Heidelberg, 363-373.
15. Kim, K. J., & Han, I. (2000). Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. Expert systems with Applications, 19(2), 125-132.
16. Roman, J., & Jameel, A. (1996). Backpropagation and Recurrent Neural Networks in Financial Analysis of Multiple Stock Market Returns. In System Sciences, 1996, Proceedings of the Twenty-Ninth Hawaii International Conference on IEEE, Vol. 2, 454-460.
17. Panda, C. and Narasimha, V., 2005, Predicting Stock Returns: An Experiment of the Artificial Neural Network in India Stock Market. South Asia Economic Journal, 7(2), 218.
18. Bary, A., 2003, A Giant Bargain, Barron’s, 83(38), 17-18.
19. Wiersema, W. H., 1998, Inventory: How Much is Too Much?. Electrical Apparatus, 51(7), 40Y42.
20. Trevino, R., and Fiona R., 2002, P/ E Ratios and Stock Market Returns, Journal of Financial Planning, 15(2), pp. 76-84.
21. Arnott, R. D., & Asness, C. S. (2003). Surprise! Higher Dividends= Higher Earnings Growth. Financial Analysts Journal, 59(1), 70-87.

22. Hykin, S., 1999, Neural Networks: A Comprehensive Foundation. Printice-Hall, Inc., New Jersey.
23. Brockwell, Peter J., and Richard A. Davis., 2002, Introduction to Time Series and Forecasting, 2nd edition, Springer, New York.
24. Goothmann, R., 2002, Multi-agent Market Modelling Based on Neural Networks, PhD Thesis, Faculty of Economics, University of Bremen, Germany.
25. Fausett, Laurene V., 1994, Fundamentals of Neural Networks: Architectures, Algorithms, and Applications, 40, Englewood Cliffs, Prentice-Hall.
26. Alpaydın, E., 2004, Introduction to Machine Learning (Adaptive Computation and Machine Learning), MIT Press, Cambridge.
27. Demuth, H., Beale, M., 1997, Neural Network Toolbox: For use with MATLAB, 4th Edition, The Math Works Inc., Natick.
28. Stergiou, C., 2001, What is a Neural Network? Surprise 96, Vol 1.
29. Perwej,Y., Perwej, A., 2012, Prediction of the Bombay Stock Exchange (BSE) Market Returns Using Artificial Neural Network and Genetic Algorithm , Journal of Intelligent Learning Systems and Applications, 4, 108-119
30. Busseti, E., Osband, I. and Wong, S., 2012, Deep Learning for Time Series Modelling. Technical Report, Stanford University.
31. http://advanced-charts.blogspot.in/2009/12/objective-of-technical-analysis.html
32. http://www.ambarasoft.com/researchservices/trendanalysis.html
33. https://jcflowers1.iweb.bsu.edu/rlo/trends.htm
34. https://in.finance.yahoo.com/q/hp?s=ADANIENT.NS
35. https://in.finance.yahoo.com/q/hp?s=COALINDIA.NS
36. https://in.finance.yahoo.com/q/hp?s=NMDC.NS
37. https://www.google.com/finance